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# Summer Student Jessica Halterman Report

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This summer I worked on the Enhanced Radiological Nuclear Inspection and Evaluation (ERNIE) project with Dr. Simon Labov. Radiation screening of vehicles is performed at ports of entry and checkpoints. Vehicles carrying cargo containing radioactive material set off an alarm. Currently, trained experts are required to evaluate each alarm. This takes time and holds up traffic. Also, the accuracy of the threat evaluation is dependent on the training of the evaluator.

Cargo can hold benign radioactive materials, naturally occurring radioactive material (NORM) or medical sources, in addition to radioactive threats. Therefore every cargo that sets off an alarm does not necessarily hold a radioactive threat. The ERNIE project seeks to improve the accuracy of threat/non-threat evaluation at these radiation screenings. This includes increasing the sensitivity of threat detection while still reducing false alarm rates.

In order to accomplish these goals, Dr. Labov and his team at Lawrence Livermore National Laboratory work on extracting features from the data collected from the Radiation Portal Monitors (RPM) that the vehicles pass through. These RPMs detect radiation in the vehicles as they pass through. A training table is compiled from these features. This training table is then sent to Carnegie Mellon University. They will use the training table to train a machine learning system. This will result in a random forest of decision trees that will be used to classify new cargo measurements.

Two other Department of Homeland Security interns worked on the project as well. At first, we worked together on learning the background information necessary for understanding our project. We studied some of the basics of radiation detection. We

also worked on coming up with an equation to model the rate of detection of a point source located in a vehicle. We had to learn how to use Matlab, as none of us were familiar with the program before this summer. After we became more familiar with the project, we divided the work into three different parts. The features that we focused on extracting from the Radiation Portal Monitor (RPM) data fell into three areas: statistics, data fitting, and Fourier transform analysis and principal component analysis. I decided to work with the data fitting part of the project.

The idea behind using the results of data fitting as features to be included in the training table was that the plots of the cargo measurements differ in shape based on what is in them. Threats are compact, whereas NORM sources have larger volumes. Equations were developed to model the shapes of the background, one point source, one extended source, and one point source and one extended source.

$$f_{point} = \int_{t_{i-1}}^{t_i} \frac{A_p y}{((x_0 - vt)^2 + y^2 + z^2)^{3/2}} dt$$

$$f_{extended} = A_d y \int_{t_{i-1}}^{t_i} \int_{x_0}^{x_0+l} \frac{A_d}{((x - vt)^2 + y^2 + z^2)^{3/2}} dx dt$$

$$f_{point \text{ and extended}} = f_{point}(A_p, x_p, y_p, z_p) + f_{distributed}(A_d, x_d, y_d, z_d, l) + \\ \propto BkgTemplate + Bkg$$

The signals from the cargo data can then be fit to these different models.

Since the data needed to be fitted to a continuous, unconstrained model, we decided to use nonlinear least squares fitting. In particular, we decided to implement the Gauss-Newton method.

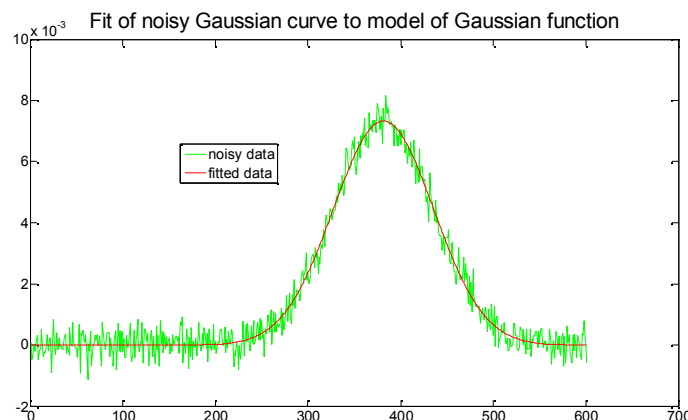
The Gauss-Newton method starts by giving the parameters of the model function initial values. These initial values are then modified by some small value in order to minimize the sum of the squared error,  $\sum (Y - f(\beta))^2$ . The general process is as follows:

1. The parameters ( $\beta$ ) to the model are given an initial value.
2. The parameters ( $\beta$ ) are adjusted by  $\Delta$  in order to minimize the sum of the squared error,  $\sum (Y - f(\beta))^2$

$$\Delta = (J_r' J_r)^{-1} J_r' (Y - f(\beta))$$

3. The process is repeated until the sum of the squared error converges.

Rather than starting by trying to fit the vehicle data to the source models, I first implemented the Gauss-Newton method by fitting a noisy Gaussian curve to the model of a Gaussian function, given by  $f(A, \mu, k) = Ae^{-k(x-\mu)^2}$ . The plot below displays the fit a noisy Gaussian curve to the model function  $f(A, \mu, k) = Ae^{-k(x-\mu)^2}$ .



In order to help ensure that the Gauss-Newton method converges, I have to come up with initial guesses for the values of the model parameters that are close to their true values. In my Matlab code, I first identify regions in the input data that might contain either a point or extended source. These regions are identified by first subtracting from the signal a smoothed copy of itself. The signal is smoothed using a simple least squares smoothing algorithm. The algorithm simultaneously solves the equations

$$y = x$$

$$x_i = x_{i+1}$$

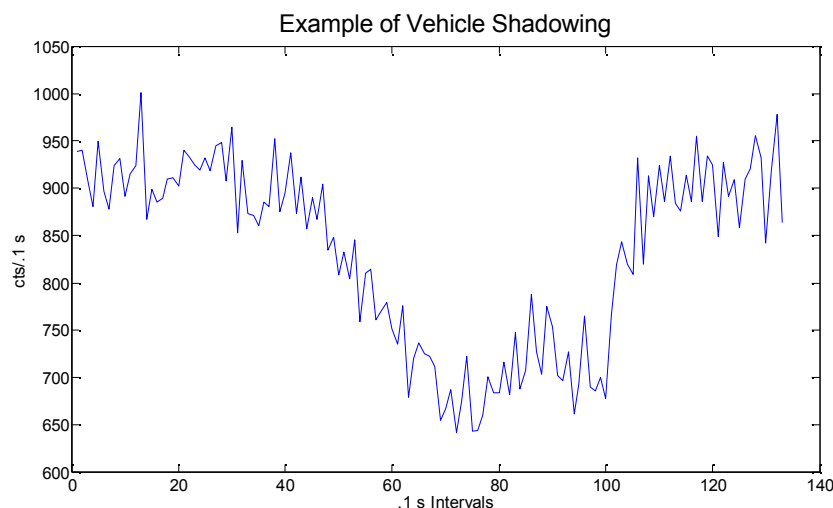
These equations assert that the data will match the smoothed copy and that adjacent points in the smoothed copy will match each other. Once the smoothed signal has been subtracted from the original signal, regions are identified in the signal by changes in the sign of the points that fall outside of a threshold of 75. This ensures that very small “bumps” in the signal are not treated as point or extended sources.

Once the regions that could contain point or extended sources are identified, each one is fit to both the point and extended source models. The region that results in the lowest error when fit to the point source model is identified as the best point source fit. Similarly, the region that results in the lowest error when fit to the extended source model is identified as the best extended source fit. If the signal contains only one region, then the best point and extended source fits occur in the same region. I do not allow this to happen if the signal contains more than one region. The source model fit that results in the greater error is reassigned to the region that results in the next lowest error. The

values for these parameters are used as the initial guesses for the parameters of the one point and one extended source model.

The signal is also fit to the background model. This background template was generated by looking at only the signals from non-alarming vehicles. The mean of the first 40 intervals of the signal, the intervals before the vehicle enters, is considered the mean background. This value is subtracted from the signal. Each vehicle signal is rebinned to a common length of 111 intervals. This includes the vehicle portion and the portion of the background intervals where the vehicle presence affects the signal. The rest of the background is disregarded. The rebinned vehicle segment is then scaled.

Once a rebinned vehicle segment is generated for each non-alarming vehicle, the average is taken of the counts in each interval. This average is then smoothed using the least squares smoothing algorithm previously mentioned. This template demonstrates the shadowing that occurs when a vehicle containing non-radioactive cargo passes through the RPM. The vehicle actually blocks the background radiation, which results in a dip in the signal, as displayed in the graph below.



Each of these fits adds features. The chi-square goodness of fit and the excess of the fit to the background only, point source, extended source, and one point and one extended source models are used as features. In addition, the mean energy of the source and the parameters of the fits to all of the source models are also features that are added to the training table. These features are combined with the features extracted from the other areas in the training table, as well as information about the manipulations performed on the data.

I also got to experience taking radiation measurements. Dr. Labov planned a road side measurement campaign that I was able to help with. We met at a parking lot and took measurements of passing vehicles using both radar and a radiation detector. A minivan, car, and truck were acquired. We took measurements of these vehicles driving by at set speeds carrying no radioactive material, unshielded sources, and shielded sources. The location of the source within the vehicles as well as the type of shielding used was varied.

I operated the software that allowed the user to view and save the measurements from the radiation detector. The vehicle drive bys were carefully choreographed so that the information about the vehicle type, speed, time, source type, shielding, etc. could be recorded. This also allowed the detection data and the radar data to be synchronized. The intern operating the radar software and I made sure to collect data at the same time, or as close as possible so that the times saved on the files would be as similar as possible. I enjoyed being able to operate the radiation detection software because it allowed me to view plots of the counts detected by the



detector in the vehicles as they passed. I was able to see how the speed and the strength of the source affected the signal shape as the vehicles passed by me.

I enjoyed being able to experience what it is like to work in a national laboratory. My housing was arranged by the intern coordinator so I ended up living with three other interns in an apartment close to the lab. This allowed me to get to know some of the other interns. I appreciated the weekly lectures sponsored by DHS. They gave me a better idea of the variety of different areas of research that DHS is involved in. The social activities coordinated by the lab such as the student barbeque and the rafting trip allowed me to meet more fellow interns. I found the tours that Lawrence Livermore National Laboratory makes available to its summer interns to be particularly interesting. There were tours available every week. I went on a tour of the National Ignition Facility. I never realized how much technology had to be developed before NIF could even be built. It was interesting, but I particularly enjoyed the tour of the Terascale Simulation Facility. It was amazing to be in the same room as the fastest computer in the world. I enjoyed learning about how the computers are built and maintained, as well as the building that houses them.

I have learned this summer that data fitting can be extremely frustrating. I had issues with the Gauss-Newton method not converging for some of the data that I attempted to fit. I looked into other options and modifications to the Gauss-Newton method, particularly using the Levenberg-Marquardt algorithm instead. It is also known as a damped least-squares method. The Levenberg-Marquardt algorithm includes a damping factor that is added to the approximation of the Hessian matrix,  $J_f' J_f$ . When the current fit is far away from the optimal fit, the algorithm behaves like the steepest

descent method. This occurs when the damping factor is large. When the current fit is close to the optimal fit, the algorithm behaves like the Gauss-Newton method. In fact, it is the Gauss-Newton method when the damping factor is equal to zero. The Levenberg-Marquardt algorithm proposes using the equation

$$\Delta = (J_r' J_r + \lambda \cdot \text{diag}(J_f' J_f))^{-1} J_r' (Y - f(\beta))$$

to describe the increment added to the parameters of the model function. I also considered changing the exit conditions of my fitting algorithm. Rather than just checking for the convergence of the sum of the squared error, I also checked if the change in the increment being added to the model parameters fell under a threshold.

I gained knowledge during this internship that could prove useful to me in the future. I became familiar with using Matlab and writing Matlab scripts, which may be useful in a future job. I also learned some basic information about nuclear radiation. I also used a lot of linear algebra during my data fitting. I have taken an introductory linear algebra course, but I have learned so much more during this project. It was useful to get experience in applying linear algebra to solve real problems.

I'm still not sure whether I plan to attend graduate school or not, but this internship has given me the opportunity to explore a job option that could exist if I were to successfully finish graduate school. Previous to this internship, I had only considered graduate school because I was interested in teaching at the university level. Now I know that there other career options available in industry or working for a national laboratory. I have learned that teaching at a university is not the only career that provides opportunities to teach and mentor students.

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